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Research Article

Event-Triggered Fault-Tolerant Control for Nonlinear Networked Control Systems

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This paper addresses the communication congestion and actuator fault in a nonlinear networked control system. A weighted average event-triggered mechanism adopted the weighted average of data packets is proposed to alleviate the communication congestion and save the network communication resources. Meanwhile, based on the system state estimation and fault estimation obtained by a state-fault observer, a fault-tolerant controller is designed to compensate and reduce the influence of fault and nonlinear factors in the networked control systems. The stability of the closed-loop system is proved by the Lyapunov–Kroasovskii theory, and the gains of the observer and controller are obtained by linear matrix inequalities. The feasibility of the proposed scheme is verified by the networked motor control system. The proposed weighted average event-triggered fault-tolerant control scheme can reduce the data transmission without affecting system performance. Meanwhile, it not only has fault-tolerant control performance but also reduces the influence of nonlinear factors on the system output.

1. Introduction

In recent decades, networked control systems (NCSs) have gradually attracted considerable attentions. Compared with conventional control systems with point-to-point wired communication, NCSs have more advantages. For example, the introduction of the network can reduce the complexity and cost of the control systems and improve the reliability and scalability of the control systems. Therefore, NCSs have been widely applied in the industrial process, automatic control, robotics, aircraft, and unmanned technology [1–3]. Nevertheless, some unfavorable factors also unavoidably appear in NCSs, such as communication congestion, actuator fault, nonlinear factors, network-induced delay, and so on, which inevitably affects the control performance [4–6].

Due to limited communication bandwidth and imperfect communication link, the communication congestion may appear in NCSs [7–9]. In order to alleviate the communication congestion and save the network communication resources, the event-triggered mechanism is usually adopted in NCSs [10–13]. Different from the conventional time-triggered sampling, the event-triggered mechanism is based on data sampling. Therefore, an event-triggered mechanism can improve the efficiency of data transmission in the communication and calculation of NCSs. In [14], an adaptive event-triggered scheme was designed to alleviate the communication congestion. In [15], a self-triggered and event-triggered mixed sampling scheme was proposed to reduce the numbers of transmitted data packets in wireless NCSs. In order to get better quality of service for network communication, a hybrid method of random switching based on time-triggered and event-triggered was introduced in [16]. Nevertheless, the possible actuator fault in NCS is ignored in [14–16].

Besides communication congestion, actuator fault is inevitable in practical NCSs which decreases the system performance. Therefore, the fault-tolerant control (FTC) of NCSs as well as event-triggered mechanism is widely studied. In [17], an adaptive event-triggered mechanism was proposed and a fault-tolerant controller based on the triggered output data was designed. In [18], a sliding mode fault-tolerant controller for NCSs was proposed under a dynamic event-triggered mechanism to ensure that the trajectories of the system can reach the sliding surface. In [19], an impulsive FTC was designed based on the estimated fault and an integral-based event-triggered mechanism was designed to alleviate communication congestion. In [20], a fault-tolerant controller based on an adaptive memory-based event-triggered mechanism was proposed to compensate for the influence of fault according to the fault estimation. In [21], based on the system state and fault estimation, a fault-tolerant controller was designed to compensate for the fault and the event-triggered mechanism was adopted to save communication resources. However, the NCSs considered in [17–21] are linear and the influence of nonlinear factors is ignored.

Along with communication congestion and possible actuator fault, the modeling of NCSs is often accompanied with some complex nonlinear factors in practice [22–24], such as the nonlinear coupling relationship among different nodes in complex dynamic networks [25] and the communication topology structure of nonlinear multiagent systems [26]. Therefore, the research of nonlinear NCSs has further significance. In [27], a resilient event-triggered mechanism was developed, and the sufficient conditions were constructed to ensure that the switched control strategy subjected to actuator fault and nonlinear factors was exponentially stable. In [28], a period event-triggered sampling scheme was designed, and an FTC was proposed for nonlinear NCSs to guarantee its stability under the actuator fault. In [29], an adaptive event-triggered communication scheme was adopted to save the network communication resources by adjusting event-triggered threshold, and a state feedback controller was designed for nonlinear NCSs under fault. In [30], an event-based adaptive FTC using a fuzzy approximation mechanism was proposed for the nonlinear system, which could also be applied to NCSs. In [31], an adaptive event-triggered mechanism with an adjustable triggering threshold was proposed, and an FTC with stochastic event-driven actuator scheduling was investigated for nonlinear NCSs. However, some unexpected triggered events can be further avoided in [27–31].

Inspired by the discussions above, in this paper, a weighted average event-triggered fault-tolerant control scheme is proposed for nonlinear NCSs subjected to communication congestion and actuator fault. The main contributions of this paper are as follows:

(1) Different from the conventional event-triggered mechanism, the weighted average event-triggered mechanism (WAETM) considers the weighted average of data packets, which can further alleviate the communication congestion and save the network communication resources.

(2) Based on the WAETM a state-fault observer is designed to obtain the system state estimation and fault estimation, which can guarantee the asymptotically stability of the observation error dynamic system.

(3) With the system state estimation and fault estimation, a fault-tolerant controller is designed, which can compensate for the influence of fault and reduce the influence of nonlinear factors in NCSs.

The remainder of this paper is structured as follows. The model of nonlinear NCSs is presented in Section 2. The design of the WAETM, state-fault observer, and fault-tolerant controller are presented, and the stability of the closed-loop system is proved in Section 3. The feasibility of the weighted average event-triggered FTC scheme for nonlinear NCSs is demonstrated by the networked motor control system in Section 4.

Notations: the following notations are adopted in this paper. I denotes the identity matrix with an appropriate dimension. For matrix B, its inverse and transpose matrices are denoted by $B^{\dagger}$ and B^T, respectively. 0 denotes zero matrix. $\mathbf{R}^n$ denotes the n-dimension Euclidean space and $\mathbf{R}^{n\times n}$ denotes the $n \times n$ matrix. $\{*\}$ denotes the symmetric term in a symmetric block matrix.

2. Problem Statement

The model of nonlinear NCSs with actuator fault is as follows:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + B_f f(t) + F\rho(x(t), t), \\ y(t) = Cx(t), \end{cases} \tag{1}$$

where $x(t) \in \mathbf{R}^n$ is the system state vector, $u(t) \in \mathbf{R}^m$ is the system control input, and $y(t) \in \mathbf{R}^r$ is the system measured output, $f(t) \in \mathbf{R}^m$ is the actuator fault, $\rho(x(t), t) = [\rho_1(x_1(t), t), \ldots, \rho_n(x_n(t), t)]^T$ is the nonlinear function, $A \in \mathbf{R}^{n\times n}, B \in \mathbf{R}^{n\times m}, C \in \mathbf{R}^{r\times n}, B_f \in \mathbf{R}^{n\times m}, F \in \mathbf{R}^{n\times n}$ are the system parameter matrices with appropriate dimensions.

Assumption 1 (See [32, 33]). It is assumed that the nonlinear function $\rho(x(t), t)$ is continuous and bounded, and satisfies Lipschitz conditions. Therefore, the following condition is satisfied

$$\left\|\rho(x_1(t), t) - \rho(x_2(t), t)\right\| \le \delta \left\|x_1(t) - x_2(t)\right\|, \tag{2}$$

where δ is the Lipschitz constant.

Assumption 2. Assume that the derivative of the fault is norm-bounded, i.e. $\|\dot{f}(t)\| \le f_\Delta$, where f_Δ is a constant.

3. Design of Weighted Average Event-Triggered Fault-Tolerant Control

The proposed weighted average event-triggered FTC scheme is shown in Figure 1. In order to save the network communication resources in nonlinear NCSs, a WAETM is designed to reduce the measured output data from $y(t)$ to $y(t_k h)$. The zero-order holder ZOH guarantees the continuity of the successfully triggered data packet $\tilde{y}(t)$ within the holding time-interval. The state-fault observer is designed to obtain the real-time system state estimation $\hat{x}(t)$ and fault estimation $\hat{f}(t)$. Finally, the fault-tolerant controller $u(t)$ is designed based on the system state estimation and fault estimation to compensate and reduce the influence caused by the fault and nonlinear factors.

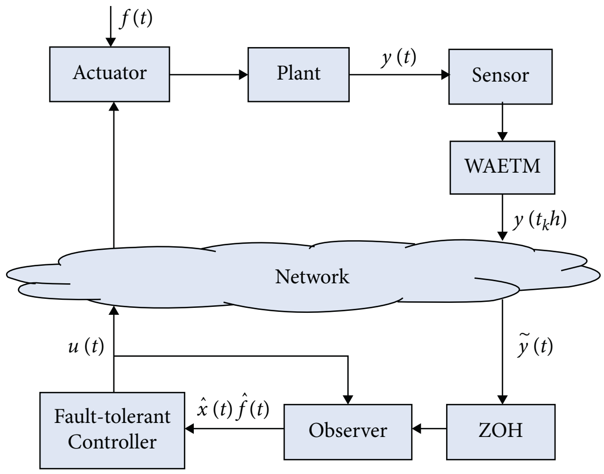

Figure 1: Weighted average event-triggered FTC scheme.

3.1. WAETM. Event-triggered mechanism is an effective way to alleviate the communication congestion and save the network communication resources. However, the conventional event-triggered mechanism depends on the difference between the values of the latest released data packet and the current sampling data packet. The conventional event-triggered mechanism is [21].

$$\begin{aligned} t_{k+1}h = t_kh + \min_{l\in\mathbb{N}^+}\{lh|e_c^T(t)\Omega e_c^T(t) \\ > \sigma y^T(t_kh+lh)\Omega y(t_kh+lh)\}, \end{aligned} \tag{3}$$

where t_kh represents the release instant, t_k is a positive integer, and h is the sampling period. l denotes the interval time between the latest triggered instant and the next triggered instant, σ is a constant, Ω is the constant weighted matrix, and $e_c(t) = y(t_kh) - y(t_kh+lh)$.

In order to further decrease the triggered data error and save the network communication resources, the WAETM is designed as follows:

$$\begin{aligned} \Psi = \{l|e^T(t)\Omega e(t) - \sigma\overline{y}^T(t_kh)\Omega\overline{y}(t_kh) \\ +\phi\sigma[\overline{y}^T(t_kh)\Omega e(t) + e^T(t)\Omega\overline{y}^T(t_kh)] \le 0\}, \end{aligned} \tag{4}$$

where Ψ denotes a set of events satisfying the event trigger condition, $\overline{y}(t_kh) = [t_khy(t_kh) + (t_kh+lh)y(t_kh+lh)]/(2t_kh+lh)$ denotes the weighted average value between the latest released data packet and the current sampling data packet, $e(t) = y(t_kh) - \overline{y}(t_kh)$ denotes the difference between the latest released data packet and the weighted average data packet, and ϕ is a constant.

Remark 1. Compared with the conventional event-triggered mechanism (2), the proposed WAETM (3) can decrease the triggered data error $e(t)$, avoiding unexpected triggered events. Meanwhile, the item $\phi\sigma[\overline{y}^T(t_kh)\Omega e(t) + e^T(t)\Omega\overline{y}^T(t_kh)]$ in the WAETM (3) contains a triggered data packet $y(t_kh)$. Therefore, the controller can obtain data packets from the network even when the system is subjected to others noises or disturbances. In fact, the WAETM in (3) can be converted into the conventional event-triggered mechanism in [21] when $\phi = 0$.

The release instant of WAETM is denoted as $t_{k+1}h = t_kh + (l_M+1)h$, where $l_M = \max\{l|l\in\Psi\}$. When the data packets are successfully transmitted to the observer, the system measured output can be written as follows:

$$\tilde{y}(t) = y(t_kh), \quad t\in[t_kh+\tau_k, t_{k+1}h+\tau_{k+1}), \tag{5}$$

where $\tilde{y}(t)$ denotes the data successfully transmitted at the triggered instant and τ_k is the time delay.

Considering that the data packets transmitted by the WAETM are subjected to time delay $\tau_k = j_k - t_kh$, where j_k represents the instant when the data packets arrive at the ZOH. The ZOH deals with the data packets out-of-sequence and guarantees the continuity of control input within the holding time-interval. The subintervals are defined as follows:

$$I = \begin{cases} I_1 = [j_k, j_k+h), \\ I_2 = [j_k+h, j_k+2h), \\ \vdots \\ I_{\overline{n}_k} = [j_k + (\overline{n}_k-1)h, j_{k+1}), \end{cases} \tag{6}$$

where $\overline{n}_k = \min\{l|j_k + (l-1)h \ge j_{k+1}\}$, and the time delay function can be written as follows:

$$\tau(t) = \begin{cases} t - t_kh, & t\in I_1, \\ t-(t_k+1)h, & t\in I_2, \\ \vdots \\ t - [t_k + (j_k-1)]h, & t\in I_{\overline{n}_k}, \end{cases} \tag{7}$$

where $0\le\tau(t)\le\tau_M$, $\dot{\tau}(t)\le\tau_\Delta$, τ_M is the maximum value of the $\tau(t)$, and τ_Δ is a constant. Then the error function of ZOH can be expressed as follows:

$$e_y(t) = \begin{cases} y(t_kh) - y(t_kh), & t\in I_1, \\ y(t_kh) - y((t_k+1)h), & t\in I_2, \\ \vdots \\ y(t_kh) - y(t_kh + (\overline{n}_k-1)h)), & t\in I_{\overline{n}_k}, \end{cases} \tag{8}$$

which implies that

$$\tilde{y}(t) = e_y(t) + y(t-\tau(t)), \quad t\in[j_k, j_{k+1}]. \tag{9}$$

3.2. State-Fault Observer. According to the data packets $\tilde{y}(t)$ successfully transmitted by the WAETM, the state-fault observer is designed as follows:

$$\begin{cases} \dot{\widehat{x}}(t) = A\widehat{x}(t) + Bu(t) + B_f\widehat{f}(t) + F\rho(\widehat{x}(t),t) + L(\widetilde{y}(t) - \widehat{y}(t-\tau(t))), \\ \dot{\widehat{f}}(t) = G\widehat{f}(t) + H(\widetilde{y}(t) - \widehat{y}(t-\tau(t))), \\ \widehat{y}(t) = C\widehat{x}(t), \end{cases} \tag{10}$$

where $\widehat{x}(t) \in \mathbf{R}^n$, $\widehat{y}(t) \in \mathbf{R}^r$, $\widehat{f}(t) \in \mathbf{R}^m$, $\rho(\widehat{x}(t),t) = [\rho_1(\widehat{x}_1(t),t),\ldots,\rho_n(\widehat{x}_n(t),t)]^T$ are the system state estimation vector, system measured output estimation, fault estimation signal, and nonlinear function estimation, respectively. L and H are observer gain matrices to be designed later.

The estimation error of system state is defined as $e_x(t) = x(t) - \widehat{x}(t)$, the estimation error of fault is defined as $e_f = f(t) - \widehat{f}(t)$, and the estimation error of nonlinear function is defined as $g(e_x(t)) = \rho(x(t)) - \rho(\widehat{x}(t))$. Then, the estimation error of system state and fault can be respectively rewritten as follows:

$$\begin{aligned} \dot{e}_x(t) &= Ae_x(t) + Fg(e_x(x)) + B_f e_f(t) - Le_y(t) \\ &\quad - LCe_x(t-\tau(t)), \\ \dot{e}_f(t) &= (1-G)f(t) + Ge_f(t) - He_y(t) \\ &\quad - HCe_x(t-\tau(t)). \end{aligned} \tag{11}$$

Define $\xi(t) = [e_x(t)e_f(t)]^T$, then the observation error dynamic system can be given as follows:

$$\dot{\xi}(t) = \overline{A}\xi(t) + \overline{B}\xi(t-\tau(t)) + \overline{L}e_y(t) + \overline{D}f(t) + \overline{F}g(e_x(t)), \tag{12}$$

where $\overline{A} = \begin{bmatrix} A & B_f \\ 0 & G \end{bmatrix}$, $\overline{B} = \begin{bmatrix} -LC & 0 \\ -HC & 0 \end{bmatrix}$, $\overline{L} = \begin{bmatrix} -L \\ -H \end{bmatrix}$, $\overline{D} = \begin{bmatrix} 0 \\ 1-G \end{bmatrix}$, $\overline{F} = \begin{bmatrix} F \\ 0 \end{bmatrix}$.

Up to now, we need some lemmas and definitions before proceeding the stability of observation error dynamic.

Lemma 1 (See [34]). For any positive definite constant matrix $Y \in \mathbf{R}^{n\times n}$, scalar $\alpha > 0$, and vector function $\dot{x}$: $[-\alpha, 0] \longrightarrow \mathbf{R}^n$, the following integration is defined:

$$-\alpha\int_{t-\alpha}^{t} \dot{x}^T(\theta)Y\dot{x}(\theta)d\theta \le \begin{bmatrix} x(t) \\ x(t-\alpha) \end{bmatrix}^T \begin{bmatrix} -Y & Y \\ * & -Y \end{bmatrix} \begin{bmatrix} x(t) \\ x(t-\alpha) \end{bmatrix}. \tag{13}$$

Definition 1 (See [35]). System (12) satisfies the H_∞ performance under initial condition, and the following performance index holds for all nonzero $f(t) \in L_2[0,\infty)$.

$$\int_0^\infty \xi^T(s)\xi(s)ds \le \lambda_1 \int_0^\infty f^T(s)f(s)ds, \lambda_1 > 0. \tag{14}$$

Theorem 1. *For given positive scalars h, τ_M, ϕ, σ, λ_1 and υ, there exists symmetric positive definite matrices $P > 0$, $R_1 > 0$, $R_2 > 0$, $R_3 > 0$, $G > 0$, $Q > 0$, and appropriate matrices M and Z such that the following condition holds.*

$$\Xi = \begin{bmatrix} \Xi_{11} & \Xi_{12} & \Xi_{13} & Q & M^T\overline{F} & Z & M^T\overline{D} \\ * & \Xi_{22} & M^T\overline{B} & 0 & M^T\overline{F} & Z & M^T\overline{D} \\ * & * & \Xi_{33} & 0 & 0 & \Xi_{36} & 0 \\ * & * & * & \Xi_{44} & 0 & 0 & 0 \\ * & * & * & * & -\upsilon I & 0 & 0 \\ * & * & * & * & * & -\Omega & 0 \\ * & * & * & * & * & * & -\lambda_1 I \end{bmatrix} < 0, \tag{15}$$

where $\Xi_{11} = R_1 + R_2 - \pi^2/4G - Q + M^T\overline{A}$, $\Xi_{12} = 2P - M^T + \overline{A}^T M^T$,

$$\begin{aligned} \Xi_{13} &= \frac{\pi^2}{4}G + \frac{\pi^2}{4}G^T + M^T\overline{B}, \\ \Xi_{22} &= \tau_M^2 G + \tau_M^2 Q, \\ \Xi_{33} &= \sigma C^T\Omega C + (1-\tau)R_2 - (1-\tau)R_1 - \frac{\pi^2}{4}G, \\ \Xi_{36} &= \phi\sigma\left(C^T\Omega + \Omega C\right), \\ \Xi_{44} &= -R_2 - R_3 - Q, \end{aligned} \tag{16}$$

then the observation error dynamic system (12) with the WAETM (4) is asymptotically stable. In addition, the state-fault observer gain matrices can be obtained by $\overline{L} = M^{-T}Z$.

Proof. Choose a Lyapunov–Krasovskii function as follows:

$$V_1(t) = V_{11}(t) + V_{12}(t) + V_{13}(t), \tag{17}$$

where

$$
\begin{aligned}
V_{11}(t) &= \xi^T(t)P\xi(t) + \int_{t-\tau(t)}^{t} \xi^T(\theta)R_1\xi(\theta)\mathrm{d}\theta + \int_{t-\tau_M}^{t-\tau(t)} \xi^T(t)R_2\xi(t) + \int_{t-\tau_M}^{t} \xi^T(\theta)R_3\xi(\theta)\mathrm{d}\theta,\\
V_{12}(t) &= \tau_M^2 \int_{i_k h}^{t} \dot{\xi}^T(\theta)G\dot{\xi}(\theta)\mathrm{d}\theta - \frac{\pi^2}{4}\int_{i_k h}^{t} [\xi(\theta) - \xi(i_k h)]^T G[\xi(\theta) - \xi(i_k h)]\mathrm{d}\theta,\\
V_{13}(t) &= \tau_M \int_{t-\tau_M}^{t}\int_{r}^{t} \dot{\xi}^T(\theta)Q\dot{\xi}(\theta)\mathrm{d}\theta\mathrm{d}r.
\end{aligned}
\tag{18}
$$

The derivative of (17) is obtained as follows:

$$
\begin{aligned}
\dot{V}_{11}(t) &= 2\xi^T(t)P\dot{\xi}(t) + \xi^T(t)R_1\xi(t) - (1-\tau)\xi^T(t-\tau(t))R_1\xi(t-\tau(t)) + (1-\tau)\xi^T(t-\tau(t))\\
&\qquad R_2\xi(t-\tau(t)) - \xi^T(t-\tau_M)R_2\xi(t-\tau_M) + \xi^T(t)R_3\xi(t) - \xi^T(t-\tau_M)R_3\xi(t-\tau_M),\\
\dot{V}_{12}(t) &= \tau_M^2\dot{\xi}^T(t)G\dot{\xi}(t) - \frac{\pi^2}{4}[\xi(t) - \xi(t-\tau(t))]^T G[\xi(t) - \xi(t-\tau(t))],\\
\dot{V}_{13}(t) &= \tau_M^2\dot{\xi}^T(t)Q\dot{\xi}(t) - \tau_M\int_{t-\tau_M}^{t} \dot{\xi}^T(\theta)Q\dot{\xi}(\theta)\mathrm{d}\theta.
\end{aligned}
\tag{19}
$$

According to Lemma 1, we can obtain the following equation:

$$
-\tau_M\int_{t-\tau_M}^{t} \dot{\xi}^T(\theta)Q\dot{\xi}(\theta)\mathrm{d}\theta \le \begin{bmatrix} \xi(t) \\ \xi(t-\tau_M) \end{bmatrix}^T \begin{bmatrix} -Q & Q \\ * & -Q \end{bmatrix} \begin{bmatrix} \xi(t) \\ \xi(t-\tau_M) \end{bmatrix}.
\tag{20}
$$

Therefore, from (19) we can get the following equation:

$$
\begin{aligned}
\dot{V}_1(t) &\le 2\xi^T(t)P\dot{\xi}(t) + \xi^T(t)\left[R_1 + R_3 - \frac{\pi^2}{4}G - Q\right]\xi(t) - \xi^T(t-\tau(t))\left[(1-\tau)R_2 - (1-\tau)R_1 - \frac{\pi^2}{4}G\right]\\
&\quad \cdot \xi(t-\tau(t)) + \xi^T(t-\tau_M)[-R_2 - R_3 - Q]\xi(t-\tau_M) + \dot{\xi}^T(t)\\
&\quad \cdot \left[\tau_M^2 G + \tau_M^2 Q\right]\dot{\xi}(t) + \xi^T(t)\left[\frac{\pi^2}{4}G + \frac{\pi^2}{4}G^T\right]\xi(t-\tau(t)) + \xi^T(t)Q\xi(t-\tau_M).
\end{aligned}
\tag{21}
$$

In addition, the WAETM (3) is equivalent to the following equation:

$$
\begin{aligned}
e_y^T(t)\Omega e_y(t) &\le \sigma y^T(t-\tau(t))\Omega y(t-\tau(t)) + \phi\sigma\left[y^T(t-\tau(t))\Omega e_y(t) + e_y^T(t)\Omega y(t-\tau(t))\right]\\
&= \sigma\xi^T(t-\tau(t))C^T\Omega C\xi(t-\tau(t)) + \phi\sigma\left[\xi^T\left(t-\tau(t)C^T\Omega e_y(t) + e_y^T(t)\Omega C\xi(t-\tau(t))\right)\right].
\end{aligned}
\tag{22}
$$

It is worth noting that for any matrix M with appropriate dimensions, we have the following equation:

$$\left[\xi^T(t)M^T + \dot{\xi}^T(t)M^T\right]\left[-\dot{\xi}(t) + \overline{A}\xi(t) + \overline{B}\xi(t-\tau(t)) + \overline{L}e_y(t) + \overline{D}f(t) + \overline{F}g(e_x(t))\right] = 0. \tag{23}$$

According to Assumption 1, the nonlinear function $\rho(x(t),t)$ satisfies the Lipschitz condition, and for any positive number υ we have the following equation:

$$\upsilon\xi^T(t)\delta^2\xi(t) - \upsilon g^T(e_x(t))g(e_x(t)) \geq 0. \tag{24}$$

Define a new function as follows:

$$J_1(t) = \dot{V}_1(t) + \xi^T(t)\xi(t) - \lambda_1 f^T(t)f(t). \tag{25}$$

Integrating both sides of (25) under the zero initial condition gives us the following equation:

$$\int_0^t J_1(s)\mathrm{d}s = V_1(t) + \int_0^t \xi^T(s)\xi(s)\mathrm{d}s - \lambda_1\int_0^t f^T(s)f(s)\mathrm{d}s, \tag{26}$$

where $V_1(t) > 0$. Then according to Definition 1, we can obtain the following equation:

$$\int_0^t \xi^T(s)\xi(s)\mathrm{d}s \leq \lambda_1\int_0^t f^T(s)f(s)\mathrm{d}s. \tag{27}$$

Define a variable as $\varpi_1(t) = [\xi^T(t)\dot{\xi}^T(t)\xi^T(t-\tau(t))\xi^T(t-\tau_M)g^T(e(x))e_y^T(t)f^T(t)]$. Then according to (21) and (25) and (27), we can get the following equation:

$$\begin{aligned} J_1(t) &= \dot{V}_1(t) + \xi^T(t)\xi(t) - \lambda_1 f^T(t)f(t) \\ &\leq \varpi_1^T(t)\Xi\varpi_1(t). \end{aligned} \tag{28}$$

According to (15) and (28), $J_1(t) < 0$ when $\Xi < 0$. When $f(t) = 0$, $\dot{V}_1(t) < 0$. Therefore, the observation error dynamic system (12) is asymptotically stable with WAETM (3). The proof of Theorem 1 is completed. □

3.3. Fault-Tolerant Controller. With the system state estimation, fault estimation, and nonlinear function estimation obtained by the sate-fault observer, the fault-tolerant controller can be designed as follows:

$$u(t) = K\widehat{x}(t) - B^{\dagger}B_f\widehat{f}(t) - B^*\rho(\widehat{x}(t)), \tag{29}$$

where K is the controller gain. The fault-tolerant controller consists of three terms. The first term $K\widehat{x}(t)$ is a state feedback control, the second term $-B^{\dagger}B_f\widehat{f}(t)$ is used to compensate the influence of faults, and the third term $-B^*\rho(\widehat{x}(t))$ is used to reduce the influence of nonlinear factors.

Combining the fault-tolerant controller (28) and the state-fault observer (10), we can obtain the following equation:

$$\begin{aligned} \dot{\widehat{x}}(t) &= A\widehat{x}(t) + BK\widehat{x}(t) - BB^{+}B_f\widehat{f}(t) - BB^*\rho(\widehat{x}(t)) + B_f\widehat{f}(t) + F\rho(\widehat{x}(t)) + L(\widetilde{y}(t) - \widehat{y}(t-\tau(t))) \\ &= (A+BK)\widehat{x}(t) + (F - BB^*)\rho(\widehat{x}(t)) + Le_y(t) + LCe_x(t-\tau(t)). \end{aligned} \tag{30}$$

According to (10) and (30), the overall closed-loop system can be written as follows:

$$\dot{\varepsilon}(t) = \widetilde{A}\varepsilon(t) + \widetilde{B}\varepsilon(t-\tau(t)) + \widetilde{L}e_y(t) + B_f e_f(t) + \widetilde{F}\varphi(\varepsilon(t)), \tag{31}$$

where $\varepsilon(t) = [\widehat{x}^T(t)e_x^T(t)]^T$, $\varphi(\varepsilon(t)) = [\rho^T(\widehat{x}(t))g(e_x^T(t))]^T$, and

$$\begin{aligned} \widetilde{A} &= \begin{bmatrix} A+BK & 0 \\ 0 & A \end{bmatrix}, \\ \widetilde{B} &= \begin{bmatrix} 0 & LC \\ 0 & -LC \end{bmatrix}, \\ \widetilde{L} &= \begin{bmatrix} L \\ -L \end{bmatrix}, \\ \widetilde{F} &= \begin{bmatrix} F - BB^* & 0 \\ F & 0 \end{bmatrix}. \end{aligned} \tag{32}$$

There needs a lemma before the subsequent discussion.

Lemma 2 (See [36]). For a fixed constant matrix Q with full column rank, the unknown matrix Y can be calculated by the following equality for any real matrix X, Y and N with appropriate dimensions:

$$Y = \left(Q^T XQ\right)^{-1}Q^T QN, \tag{33}$$

when the following condition satisfies the following equation:

$$XQY = QN. \tag{34}$$

Theorem 2. *For given positive scalars h, τ_M, ϕ, σ, λ_2 and μ, there exist symmetric positive definite matrices $P_1 > 0$, $S_1 > 0$, $S_2 > 0$, $S_3 > 0$, $H > 0$, $W > 0$. Then, suppose there exists matrix Λ, event-triggered weighted matrix $\Omega > 0$, and matrices M_1 and Θ with appropriate dimensions such that the following condition holds:*

$$\Pi=\begin{bmatrix}\prod_{11} & \prod_{12} & \prod_{13} & W & M_1^T\widetilde{F} & M_1^T\widetilde{L} & M_1^T B_f\\ * & \prod_{22} & M_1^T\widetilde{B} & 0 & M_1^T\widetilde{F} & M_1^T\widetilde{L} & M_1^T B_f\\ * & * & \prod_{33} & 0 & 0 & \prod_{36} & 0\\ * & * & * & \prod_{44} & 0 & 0 & 0\\ * & * & * & * & -\mu I & 0 & 0\\ * & * & * & * & * & -\Omega & 0\\ * & * & * & * & * & * & -\lambda_2 I\end{bmatrix}<0, \quad (35)$$

where $\prod_{11}=S_1+S_2-\pi^2/4H-W+M_1^T\widetilde{A}$, $\prod_{12}=2P_1-M_1^T+\widetilde{A}^TM_1^T$,

$$\prod_{13}=\frac{\pi^2}{4}H+\frac{\pi^2}{4}H^T+M_1^T\widetilde{B},$$
$$\prod_{22}=\tau_M^2H+\tau_M^2W,$$
$$\prod_{33}=\sigma C^T\Omega C+(1-\tau)S_2-(1-\tau)S_1-\frac{\pi^2}{4}, \quad (36)$$
$$\prod_{36}=\varphi\sigma\left(C^T\Omega+\Omega C\right),$$
$$\prod_{44}=-S_2-S_3-W,$$

then, the overall closed-loop system (31) is asymptotically stable under the WAETM with the controller gain designed as $K=(B^T\Theta B)^{-1}B^TB\Lambda$.

Proof. According to Lemma 2, if condition $\Theta BK=B\Lambda$ is satisfied, one can obtain that

$$K=\left(B^T\Theta B\right)^{-1}B^TB\Lambda, \quad (37)$$

whereafter, choose a Lyapunov-Krasovskii function as follows:

$$V_2(t)=V_{21}(t)+V_{22}(t)+V_{23}(t), \quad (38)$$

where

$$\begin{aligned}V_{21}(t)&=\varepsilon^T(t)P_1\varepsilon(t)+\int_{t-\tau(t)}^{t}\varepsilon^T(\theta)S_1\varepsilon(\theta)d\theta\\&\quad+\int_{t-\tau_M}^{t-\tau(t)}\varepsilon^T(t)S_2\varepsilon(t)+\int_{t-\tau_M}^{t}\varepsilon^T(\theta)S_3\varepsilon(\theta)d\theta,\\ V_{22}(t)&=\tau_M^2\int_{i_kh}^{t}\dot{\varepsilon}^T(\theta)H\dot{\varepsilon}(\theta)d\theta-\frac{\pi^2}{4}\int_{i_kh}^{t}[\varepsilon(\theta)-\varepsilon(i_kh)]^T\\&\quad\cdot H[\varepsilon(\theta)-\varepsilon(i_kh)]d\theta,\\ V_{23}(t)&=\tau_M\int_{t-\tau_M}^{t}\int_r^t\dot{\varepsilon}^T(\theta)W\dot{\varepsilon}(\theta)d\theta\, dr,\end{aligned} \quad (39)$$

and the derivative of (39) is obtained as follows:

$$\begin{aligned}\dot{V}_{21}(t)&=2\varepsilon^T(t)P_1\dot{\varepsilon}(t)+\varepsilon^T(t)S_1\varepsilon(t)\\&\quad-(1-\tau)\varepsilon^T(t-\tau(t))S_2\varepsilon(t-\tau(t))+(1-\tau)\varepsilon^T(t-\tau(t))S_2\varepsilon(t-\tau(t))\\&\quad-\varepsilon^T(t-\tau_M)S_2\varepsilon(t-\tau_M)+\\&\quad\varepsilon^T(t)S_3\varepsilon(t)-\varepsilon^T(t-\tau_M)S_3\varepsilon(t-\tau_M),\\ \dot{V}_{22}(t)&=\tau_M^2\dot{\varepsilon}^T(t)H\dot{\varepsilon}(t)-\frac{\pi^2}{4}[\varepsilon(t)-\varepsilon(t-\tau(t))]^TH[\varepsilon(t)-\varepsilon(t-\tau(t))],\\ \dot{V}_{23}(t)&=\tau_M^2\dot{\varepsilon}^T(t)W\dot{\varepsilon}(t)-\tau_M\int_{t-\tau_M}^{t}\dot{\varepsilon}^T(\theta)W\dot{\varepsilon}(\theta)\mathrm{d}\theta.\end{aligned} \quad (40)$$

According to Lemma 1, we can obtain the following equation:

$$-\tau_M\int_{t-\tau_M}^{t}\dot{\varepsilon}^T(\theta)W\dot{\varepsilon}(\theta)\mathrm{d}\theta\le\begin{bmatrix}\varepsilon(t)\\ \varepsilon(t-\tau_M)\end{bmatrix}^T\begin{bmatrix}-W & W\\ * & -W\end{bmatrix}\begin{bmatrix}\varepsilon(t)\\ \varepsilon(t-\tau_M)\end{bmatrix}. \quad (41)$$

Then, from (40) we can get the following equation:

$$\begin{aligned}\dot{V}_2(t) &\leq 2\varepsilon^T(t)P_1\dot{\varepsilon}(t) + \varepsilon^T(t)\left[S_1 + S_3 - \frac{\pi^2}{4}H - W\right] \\ &\cdot \varepsilon(t) - \varepsilon^T(t-\tau(t))\left[(1-\tau)S_2 - (1-\tau)S_1 - \frac{\pi^2}{4}H\right] \\ &\cdot \varepsilon(t-\tau(t)) + \varepsilon^T(t-\tau_M)\left[-S_2 - S_3 - W\right]\varepsilon(t-\tau_M) \\ &+ \dot{\varepsilon}^T(t)\left[\tau_M^2 H + \tau_M^2 W\right]\dot{\varepsilon}(t) + \varepsilon^T(t)\left[\frac{\pi^2}{4}H + \frac{\pi^2}{4}H^T\right]\varepsilon(t-\tau(t)) + \varepsilon^T(t)W\varepsilon(t-\tau_M).\end{aligned} \tag{42}$$

Again, the WAETM (4) is equivalent to the following equation:

$$\begin{aligned}e_y^T(t)\Omega e_y(t) &\leq \sigma y^T(t-\tau(t))\Omega y(t-\tau(t)) + \phi\sigma\left[y^T(t-\tau(t))\Omega e_y(t) + e_y^T(t)\Omega y(t-\tau(t))\right] \\ &= \xi^T(t-\tau(t))C^T\Omega C\xi(t-\tau(t)) + \phi\sigma\left[\xi^T(t-\tau(t)C^T\Omega e_y(t) + e_y^T(t)\Omega C\xi(t-\tau(t))\right].\end{aligned} \tag{43}$$

It is worth noting that for any matrix M_1 with appropriate dimension, we have the following equation:

$$\left[\varepsilon^T(t)M_1^T + \dot{\varepsilon}^T(t)M_1^T\right]\left[-\dot{\varepsilon}(t) + \widetilde{A}\varepsilon(t) + \widetilde{B}\varepsilon(t-\tau(t)) + \widetilde{L}e_y(t) + B_f e_f(t) + \widetilde{F}\varphi(\varepsilon(t))\right] = 0. \tag{44}$$

According to Assumption 1, the nonlinear function $\rho(x(t),t)$ satisfies the Lipschitz condition, and for any positive number μ we have the following equation:

$$\mu\varepsilon^T(t)\delta^2\varepsilon(t) - \mu\varphi^T(\varepsilon(t))\varphi(\varepsilon(t)) \geq 0. \tag{45}$$

Define a new variable as $\varpi_2(t) = [\varepsilon^T(t)\dot{\varepsilon}^T(t)\varepsilon^T(t-\tau(t))\ \varepsilon^T(t-\tau_M)\varphi^T(\varepsilon(x))e_y^T(t)e_f^T(t)]$. Then according to (42) and (45), we can get the following equation:

$$J_2(t) = \dot{V}_2(t) + \varepsilon^T(t)\varepsilon(t) - \lambda_2 e_f^T(t)e_f(t). \tag{46}$$

Similar to the proof of Theorem 1, we can obtain the following equation:

$$J_2(t) \leq \varpi_2^T(t)\prod\varpi_2(t). \tag{47}$$

According to (47), for any small scalar $\beta > 0$ under the initial condition, the following inequality holds:

$$J_2(t) \leq -\beta\|\varepsilon(t)\|^2. \tag{48}$$

According to (35) and (47), it is obvious that $J_2(t) < 0$when $\prod < 0$. Also, (48) indicates $\lim_{t\longrightarrow\infty}\|\varepsilon(t)\|^2 = 0$ and hence the closed-loop system (31) is asymptotically stable with WAETM (4). The proof of Theorem 2 is completed. □

4. Results

In this section, the networked motor control system shown in Figure 2 is adopted to verify the effectiveness of the proposed weighted average event-triggered FTC scheme. The mathematical model of the brushless direct current motor is

$$\begin{aligned}A &= \begin{bmatrix} 0 & 1.000 \\ -5.867 & -3.038 \end{bmatrix}, \\ B &= \begin{bmatrix} 0.340 \\ 4.868 \end{bmatrix}, \\ C &= \begin{bmatrix} 1 & 0 \end{bmatrix}, \\ F &= \begin{bmatrix} -0.818 & -1.65 \\ -0.2 & -0.02 \end{bmatrix}, \\ B_f &= \begin{bmatrix} -4.811 \\ -25.852 \end{bmatrix}.\end{aligned} \tag{49}$$

The control input of the motor is the voltage value. The system measured output of the motor is the speed (r/min). The reference input function is set as $y_r(t) = 400\sin(t) + 1200$, and the nonlinear function is $\rho(x(t),t) = [40\sin(x(t))0]^T$. The delay is

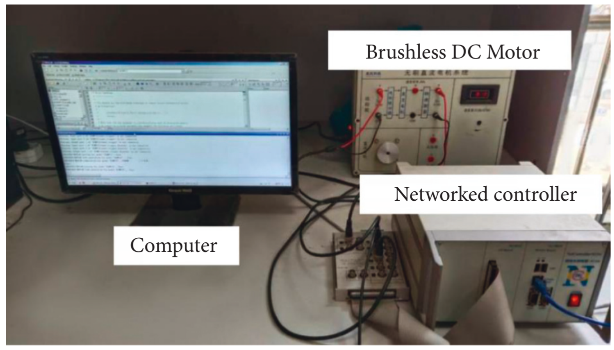

Figure 2: Brushless direct current networked motor control system.

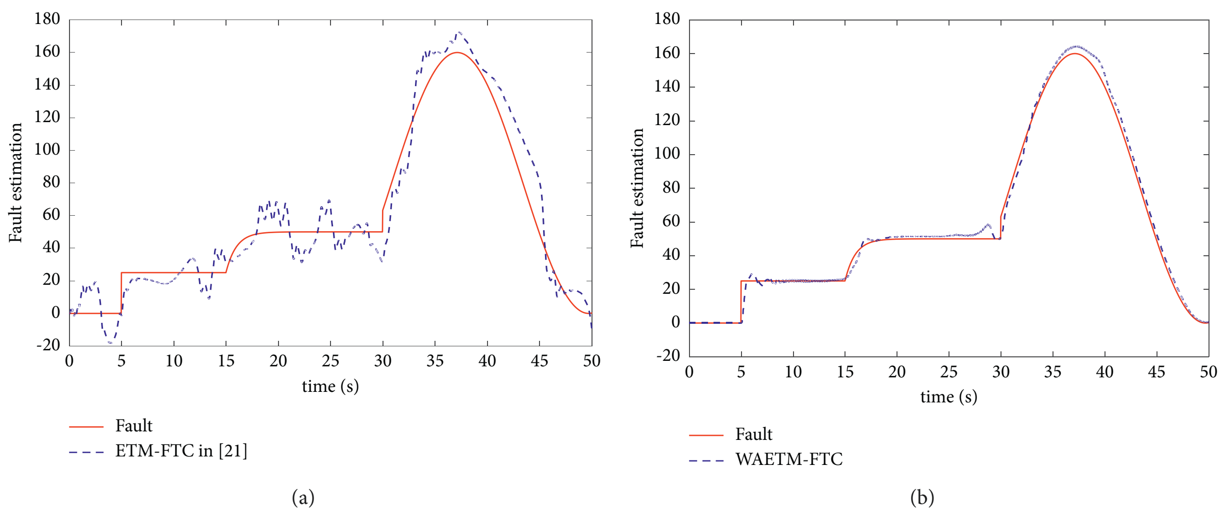

Figure 3: Fault estimation (a) ETM-FTC in [21]; (b) WAETM-FTC.

$\tau(t) = 0.2\sin(\pi t)$, and hence $\tau_M = 0.2$, $\tau_\Delta = 0.2$. In addition, parameters in the event-triggered mechanism are set as $\sigma = 0.0015$, and $\phi = 0.12$. The sampling time is $h = 0.02s$. The event-triggered weighted matrix here is set as $\Omega = I$.

According to Theorem 1 and Theorem 2, the gains of the state-fault observer and the fault-tolerant controller can be obtained as follows:

$$\begin{aligned} L &= \begin{bmatrix} 49.522 \\ -26.896 \end{bmatrix}, \\ H &= -10.982, \\ K &= \begin{bmatrix} -2.5 & -0.264 \end{bmatrix}. \end{aligned} \tag{50}$$

Other parameters of the state-fault observer and the fault-tolerant controller are

$$\begin{aligned} G &= 0.2, \\ B^{\dagger} &= \begin{bmatrix} 0.014 & 0.204 \end{bmatrix}, \\ B^{*} &= \begin{bmatrix} -0.271 & -0.232 \end{bmatrix}. \end{aligned} \tag{51}$$

Besides, the actuator fault signal is considered as follows:

$$f(t) = \begin{cases} 25, & 5 \le t < 15, \\ 50 - 25e^{(-t+15)}, & 15 \le t < 30, \\ 80 + 80\cos(0.1(t-30)), & 30 \le t < 50, \\ 0, & \text{otherwise}. \end{cases} \tag{52}$$

The scheme proposed in this paper (denoted by WAETM-FTC) is compared with the scheme in [21] (denoted by ETM-FTC). In [21], an FTC scheme was proposed, however, the conventional event-triggered mechanism was utilized and the influence of the nonlinear factors in NCSs were not considered.

Figures 3 and 4 show the fault estimation and fault estimation error, respectively. Compared with the ETM-FTC in [21], when WAETM-FTC is employed it is obvious that the fault can be estimated much better in the networked motor control system.

As shown in Figure 5, when WAETM-FTC is employed the nonlinear function can also be effectively estimated. In contrast, the ETM-FTC in [21] does not consider nonlinear factors and thus the nonlinear function estimation is not shown here.

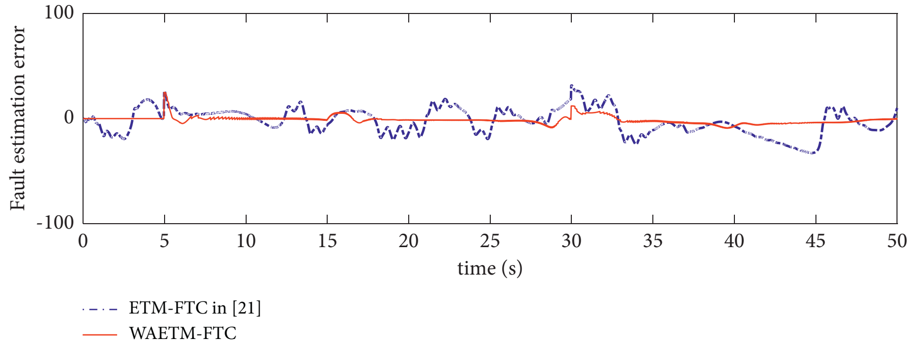

FIGURE 4: Fault estimation error.

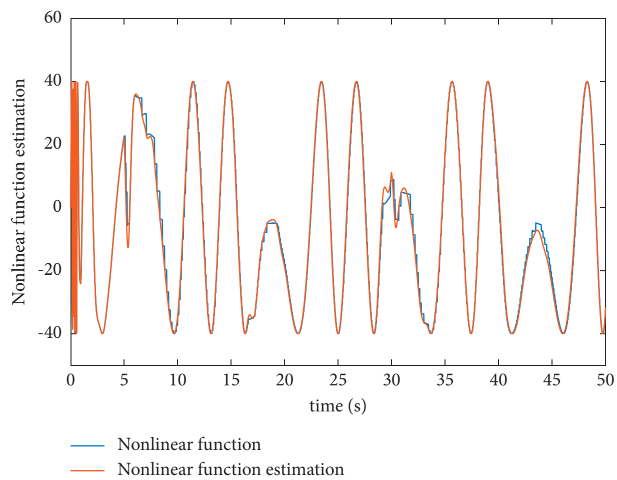

FIGURE 5: Nonlinear function estimation.

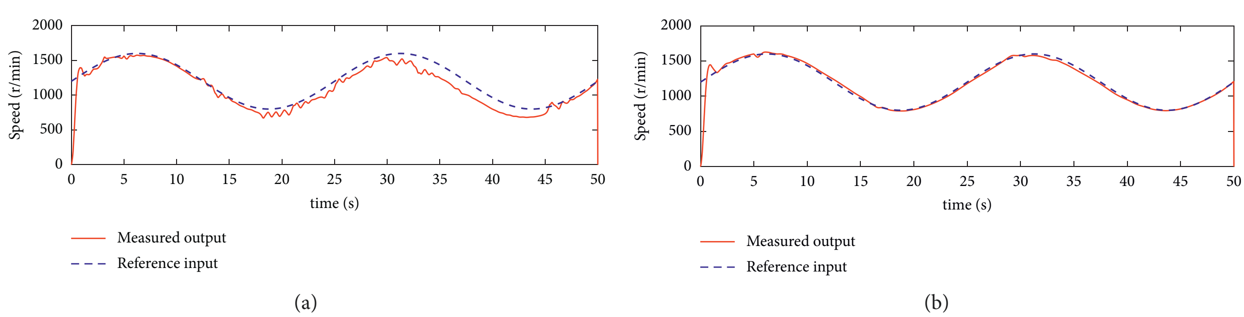

FIGURE 6: Measured output and reference input (a) ETM-FTC in [21]; (b) WAETM-FTC.

Figure 6(a) shows the measured output (speed) with the ETM-FTC in [21]. During 0-5second, although there is no fault in the system, the measured output can not track the reference input well because there are still nonlinear factors in the system. After 5 seconds, the fault occurs and the system measured output suffers from both fault and nonlinear factors. Therefore, the error between the measured output and the reference input becomes even larger as shown in Figure 7. Figure 6(b) shows the measured output (speed) with the WAETM-FTC scheme. During 0–5 seconds when the fault does not occur while there are nonlinear factors, the measured output can track the reference input. After 5 seconds, even though there are both fault and nonlinear factors in the system, the measured output can still track the reference input well. Therefore, the error between the measured output and the reference input can converge in Figure 7.

The release intervals are shown in Figure 8, when the ETM-FTC in [21] is adopted, most of the release intervals are the same with the sampling time of 0.02 seconds, which may lead to the communication congestion. In contrast, when WAETM-FTC is adopted, it is clearly that most of the release intervals are larger than 0.02 seconds, which indicates that the unnecessary transmitted data packets are reduced.

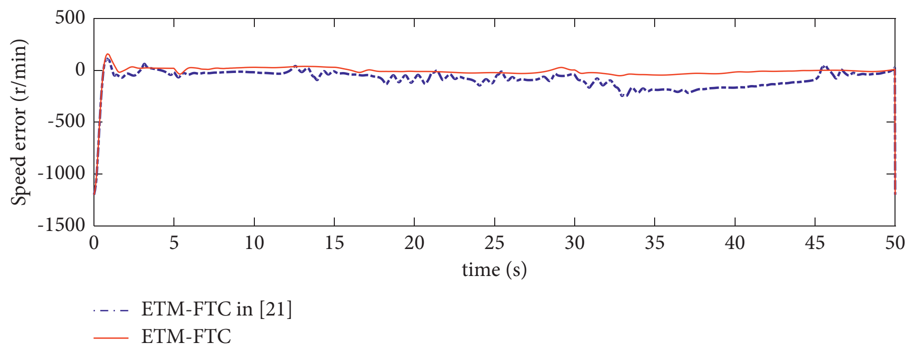

FIGURE 7: Measured output error.

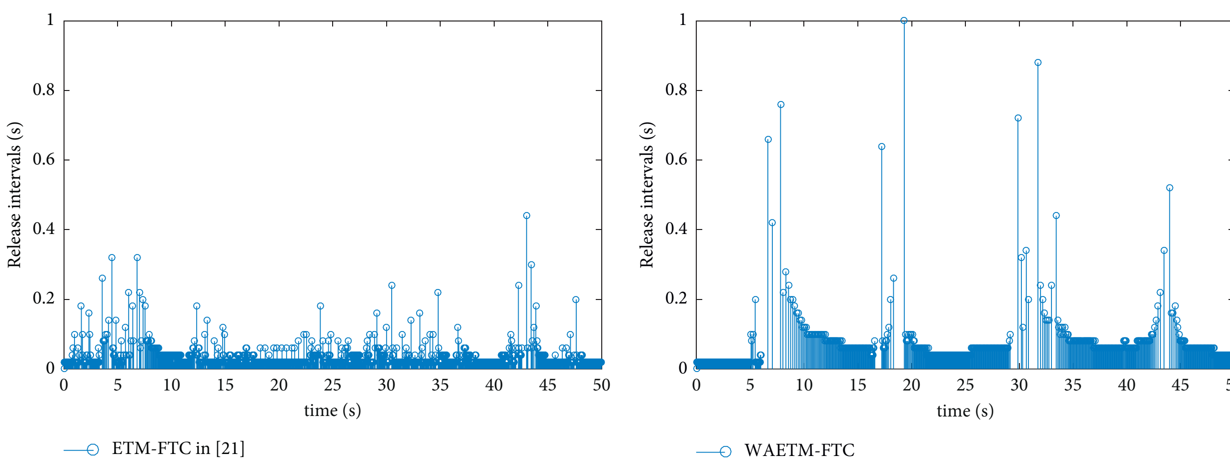

FIGURE 8: Release intervals (a) ETM-FTC in [21]; (b) WAETM-FTC.

Moreover, the triggered times are 1688 in Figure 8(a), and the triggered times are 837 in Figure 8(b), which indicates that the proposed WAETM can decrease the triggered data packets by 34.04%. Therefore, the communication congestion is effectively alleviated.

5. Conclusions

In this paper, a weighted average event-triggered fault-tolerant control scheme is proposed for nonlinear NCSs with the communication congestion and actuator fault. The weighted average event-triggered mechanism, which adopts the weighted average of data packets, is to alleviate the communication congestion and save the network communication resources. The state-fault observer based on the weighted average event-triggered mechanism is to estimate the system state and fault. With the system state estimation and fault estimation, the fault-tolerant control law is obtained. The proposed weighted average event-triggered fault-tolerant control scheme can effectively save the network communication resources in nonlinear NCSs, while compensating the influence of the fault and reducing the influence of nonlinear factors. Adaptive event-triggered based fault-tolerant control for nonlinear networked control systems will be investigated in our future work.

Data Availability

The data that support our manuscript conclusions are some open access articles that have been properly cited, and the readers can easily obtain these articles to verify the conclusions.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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